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Techniques to Enhance Assessment and Reporting of Pest Damage Estimated with Aerial Detection Surveys

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Executive Summary

Forest Health Protection (FHP) is mandated to report on the health of public, tribal, and private forest lands within the United States. Aerial detection surveys (ADS) are currently the best-available source of data used by FHP to report forest damage and pest activity trends. However, these data have limitations. ADS collect data with observations rather than direct measurements, damage severity estimates are confounded with the spatial footprint mapped, and damage severity estimation bias has been documented.

Overall, this paper presents a data-based justification for post-processing geoprocessing techniques to improve ADS data quality, reporting, and analyses. These methods are intentionally conservative to ensure damage and pest activity are not overestimated for end-users. In effect, these methods 1) respect the severity information collected by surveyors; 2) adjust for fly/no fly imbalances with underlying data for trend assessment; 3) are flexible to calculate trends at any spatial scale (subwatershed, County, Forest, Congressional District, Region, etc.); and 4) were built to enable inclusion of other remote/ground sensed damage with ADS data for trend assessments.

Methods are progressive through multiple steps to reduce importance of errors associated with observational data collection. First, ADS damage intensity estimates are collapsed into broad severity classes to reduce estimation bias. Then, a severity-weighted area statistic is calculated from severity classes to facilitate trend comparisons. Comparisons occur at subwatershed or greater spatial extent to reduce location attribution errors only for areas sufficient ADS coverage overlap. Finally, severity-weighted damages are aggregated for multi-year outbreak impact estimations.

Broad severity classes provide a qualitative framework to combine differing pest damage collection variables (trees per acre, percent mortality, remotely sensed canopy cover loss, etc.). This framework is especially beneficial to merge historic and new ADS variables (trees per acre vs. percent mortality) and methods have been validated using empirical, field-sampled research data (n = 329 plots; 30,386 trees surveyed) to be 84% accurate.

A severity-weighted area statistic is recommended for trend comparisons due to limitations with traditional footprint-area summation data. Footprint-area totals ignore severity information collected in ADS and include both areas of damage and non-damage within footprint extents. Further, footprint

extents to capture damages vary based on situational realities at the time of mapping and surveyor preference. As such, trend assessment with footprint-area totals can be misleading or invalid. Severity-weighted area summations adjust for these realities and reduce non-damaged portions of footprint-areas to enable reasonable trend and cumulative mortality assessment and can be used for subsequent statistical analyses.

Introduction

Monitoring and reporting of forest health and pest activities is required for U.S. Forest Service, Forest Health Protection programs. Information to meet requirements are produced through data collected via annual aerial detection survey (ADS) flights. Other remote sensing techniques, such as satellite imagery, have shown promise to detect vegetative change; however, these technologies have limitations in detecting low-intensity damage levels along with discerning between numerous, often subtle, agent-specific damages that aerial survey technicians are trained to recognize (McConnell et al. 2000; Wulder et al. 2006; Meddens et al. 2012) from the air. Currently, ADS is the best-available information to monitor insect pest activity and trends over vast landscape scales. However, these data have limitations.

Aerial survey data are collected on an annual basis to provide for broad-scale forest pest presence, impact, and trajectory information. Data are collected through observational means rather than direct measurements. Limited quality checks are conducted to ensure data meets nationally regulated quality standards (Forest Service Aviation Quality Assurance). However, data collected are not validated to the point where standard errors and statistical bounds on observations can be determined.

Error in aerial survey data estimations can occur within the following:

- Spatial extent attributed to damage (point/polygon size or area)
- Spatial location of damage (point/polygon location, spatial location of damage boundary)
- Damage severity estimated (total trees within polygon or per acre for mortality estimates)
- Damage agent attributed (damaging species or abiotic agent)
- Identification of damage where none exists (error of omission or false positive)
- Failure to identify damage where it does exist (errors of commission or false negative)

Studies that have assessed precision and accuracy to validate ADS data integrity are rare. Conclusions from limited studies assessing ADS error through ground surveys and/or photo interpretation indicate coarse-scale assessments appear reasonable while fine-scale analyses are lacking due to variable accuracies of damage location attributions (Johnson and Ross 2008). Furthermore, comparisons of multi-year ADS data to satellite-derived damage have suggested bias within the ADS estimates related to damage severity underestimation and/or errors of omission (Meddens et al. 2012; Backsen and Howell 2013; Coleman et al. 2018). While an underestimation bias has been commonly documented with ADS data, overestimation of damage occurs during data collection as well (Coleman et al. 2018). Unfortunately, direct validation of ADS data integrity across wide geographic extents is difficult as the remote sensing datasets used as ‘truth’ in comparison efforts have inherent limitations.

Readily available remote sensing datasets, such as satellite-derived LandsatTM ($30m^2$ pixel resolution) and MODIS ($240m^2$), have difficulty detecting low-intensity damages such as those caused by endemic or incipient bark beetle populations (Byer and Jin 2017). For these detections, spatial resolutions from potentially expensive data sources that approach $5m^2$ would be required (Wulder et al. 2005; White et al. 2005; Wulder et al. 2006). Algorithms to process data can also have difficulty discerning subtle mortality agent signatures (e.g. subalpine fir mortality vs. mountain pine beetle-caused lodgepole pine mortality) (Wulder et al. 2006). Furthermore, algorithms to detect disturbance signatures in remotely sensed data across Regional or National scales can be computationally extensive and require license purchases from cloud-based computing environments such as Google Earth Engine (Gorelick et al. 2017). As such, ADS is expected to be the primary means of forest health monitoring until technological and economic feasibility improves for other remotely sensed data sources.

Methods to reduce estimation bias were underway when this paper was written in 2017. These include changing the primary damage severity (which is synonymous with intensity for the purposes of this paper) information collected from a tree $acre^{-1}$ value to a percent of trees $area^{-1}$ value (FHAAST 2016; FHAAST 2017). These changes have led to concerns about the continuity of forest health information between historic and modern data collection methods.

This report documents additional post-processing methodologies to reduce estimation biases within the ADS data. These procedures were derived from bias-reduction techniques used for observational data collected in various ecological fields of study, most notably wildlife point-surveys that estimate avian populations (Wintle et al. 2004; Farnsworth et al. 2005). Specifically, these methods are beneficial to 1) calculate statistics that respect the limitations of observational ADS data and 2) enable a bridge for continuity between historic, current, and future damage variables while providing a qualitative framework that can support merging ADS damage estimates with other remotely sensed sources.

Products derived from methods presented have been beta-tested by Forest Health Protection staff in multiple Regions and have been refined with land manager feedback to provide reporting, monitoring, and analysis utility. While these methods focus on ADS geoprocessing steps, they can be readily adapted for other remotely sensed sources of forest pest detection and can facilitate hybridizing information from separate sources including ADS, satellite remote sensing, aerial photography, and/or ground-based observations (Long and Lawrence 2016).

Overall, our goal for this report was to provide technical geospatial processing steps to enhance ADS data quality while promoting useful products for end-users. We created these with the intention of producing conservative damage estimates rather than liberal overestimations. Our specific objectives were to build geoprocessing operations that:

1. Strategically enhance the quality of ADS data to meet monitoring requirements;
2. Provide for reasonable pest activity trend comparisons over space and/or time;
3. Estimate and display cumulative pest damages across multi-year outbreak periods.

Section 1: Methods to Reduce Estimation Bias and Enhance Monitoring Reports

- Forest health estimates of damage severity within ADS data are not rigorously validated and incorporate estimation biases.
- Damage severity estimates can be improved by collapsing data into broad qualitative severity categories to reduce estimation errors and bias.
- Reporting utility can be enhanced by including area impacted by severity class within tables and maps for display.

Damage severity estimates are often excluded from reporting due to estimation bias with ADS data estimates (see Introduction). Collapsing quantitative estimates recorded by surveyors into broad, qualitative impact classes (low, moderate, high) reduces the importance of estimation biases, presents information in a manner that is relevant to land managers, and categorizes data in manner that can facilitate a cross-walk between different data collection variables (i.e. trees per acre^{-1}, percent mortality, and satellite-derived data).

Severity classes are categorized by damage ranges that are useful for resource managers (Egan et al. 2014; Table 1). Classes can be used for any damage type (mortality, topkill, etc.) in which damage severities are estimated (see Appendix A for ADS data processing steps). Classes were initially derived by Canadian Forest Service to describe bark beetle outbreak severity (Van-Sickle et al. 2001; Taylor et al. 2006). While these classes represent best-available science, end-users can easily modify display settings to represent impacts for a given pest agent (such as an exotic where even low damage severities have a 'high' impact) and/or to improve estimations based on local knowledge.

Qualitative severity classes are beneficial as they enhance ability to estimate similar 'impact' levels from divergent data sources. Specifically, data from slightly different collection variables (i.e. trees per acre vs. percent mortality), converted into similar low, moderate, and high classes, can provide a cross-walk between historic and modern ADS variables collected. Taken further, these techniques also support inclusion of remotely sensed imagery data (from aerial photography, satellites, etc.) into 'impact' classes to hybridize forest health monitoring surveys from multiple sources.

An empirical analysis was performed to determine an appropriate crosswalk between historic (trees per acre) and modern (percent mortality) ADS collection variables to assign pest damages into the severity classes (depicted in Table 1). For this, the relationship of trees per acre to percent damage values was statistically modeled with data from 329 fixed-area ground plots that surveyed >30,000 trees after exposure to bark beetle-caused tree mortality (Figure 1; see Appendix B for comprehensive analysis methods and results). Then, modeling findings were used to determine a conservative value for low, moderate, and high impact class ranges (depicted in Table 1). Finally, ranges determined by modeling were validated to have overall 84% accurate placement of trees per acre values were within the correct percent-based low, moderate, or high impact categories. Surprisingly, this analysis indicated trees per acre ranges were equivalent to percent class ranges.

Table 1: Table identifies qualitative severity classes defined by percent mortality ranges used for collapsing ADS estimates into broad categories.

Severity Class	Trees per Acre Mortality (TPA)	Percent Mortality	Percent Midpoint
Low	< 10 TPA	< 10%	5%
Moderate	10-30 TPA	10-30%	20%
High	> 30 TPA	> 30%	65%

After collapsing ADS observations into severity classes, data quality can be enhanced further by calculating totals across a broad spatial extent (i.e. subwatershed, County, Region, or greater) to reduce the importance of spatial attribution errors. At this scale, total footprint acres can be presented in conjunction with acres by severity class (Table 2). Similarly, maps that traditionally have displayed spatial footprint of area impacted by pest can be improved with simple severity class stratifications useful for resource managers (see Map 1a vs 1b).

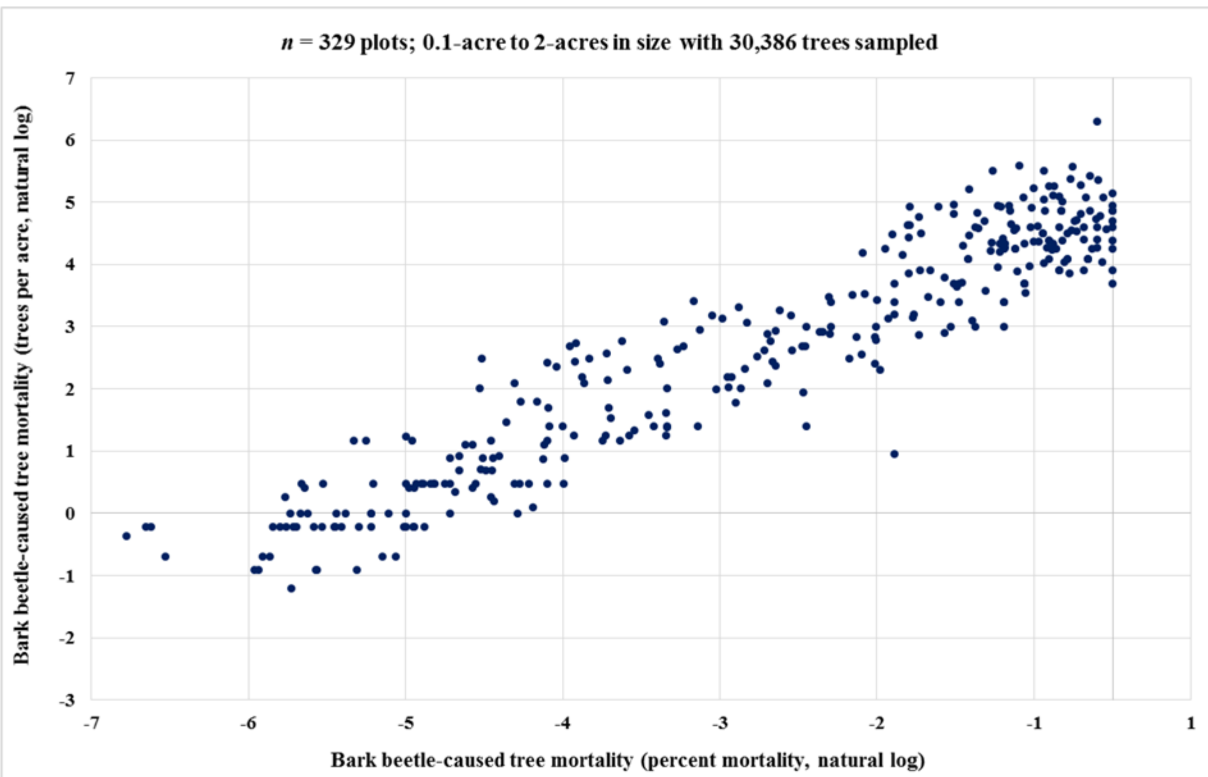
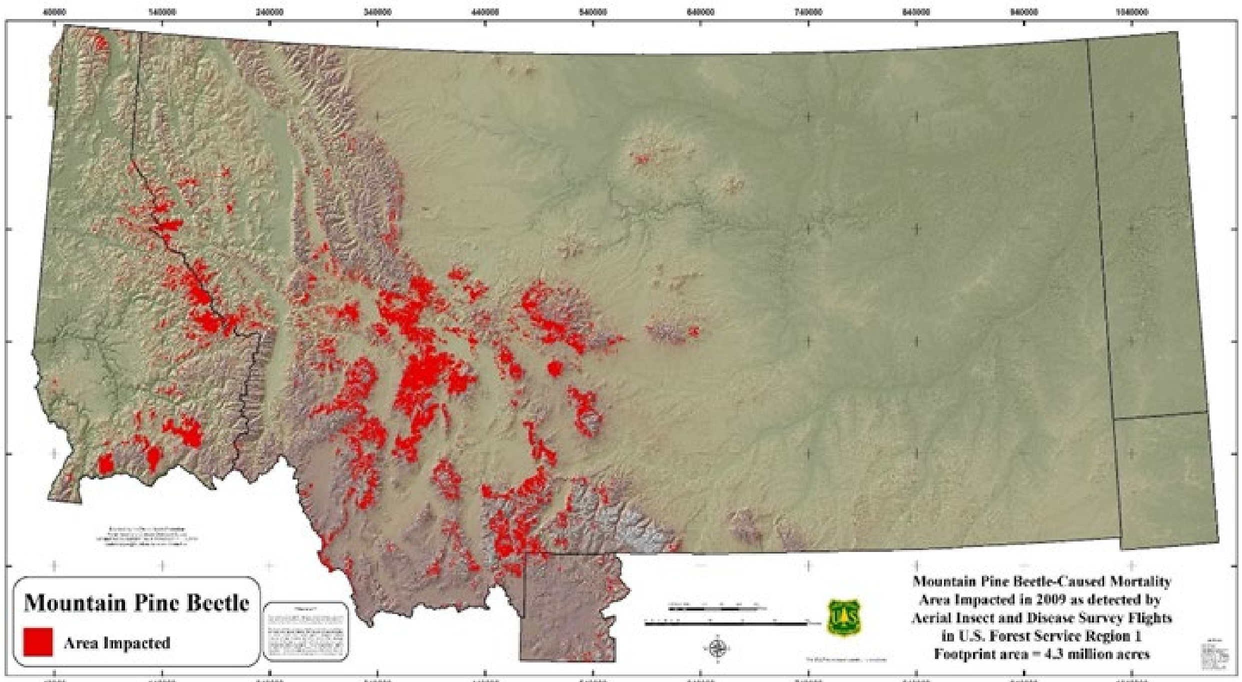
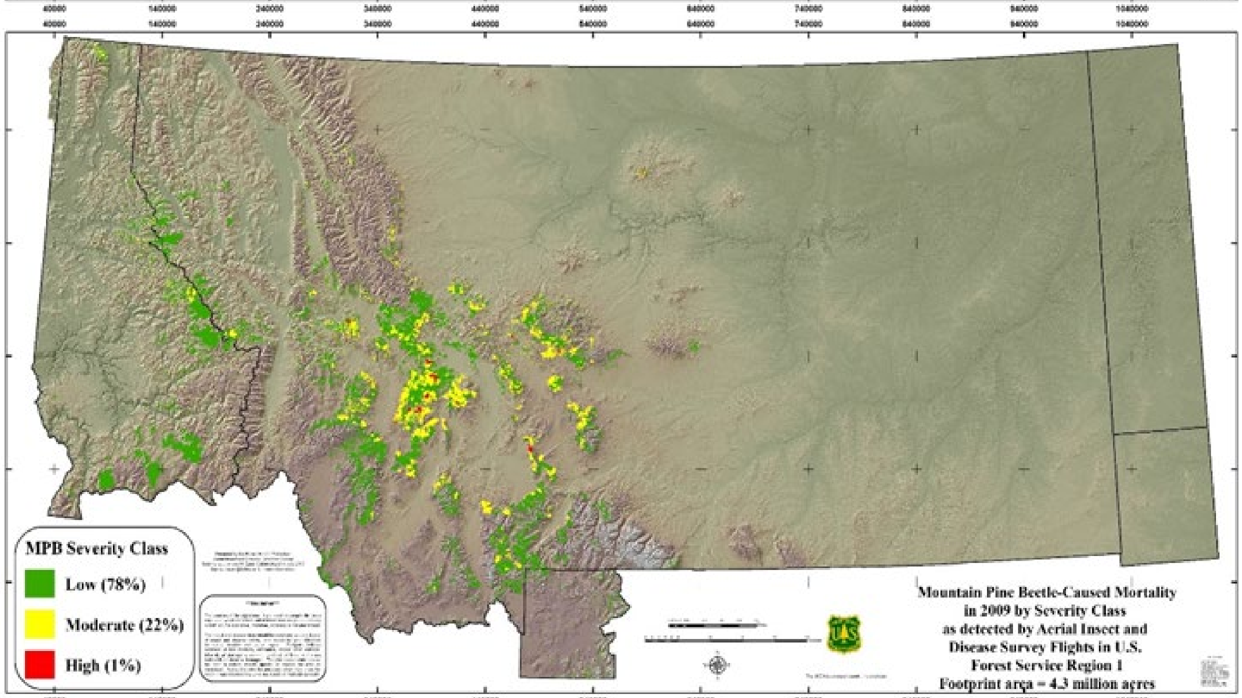


Figure 1: Relationship of trees per acre and percent mortality damage measured in yellow pine research plots exposed to Dendroctonus spp. pressure across the western United States. The strong association of these variables made it possible to create a cross-walk between trees per acre and percent mortality.





Maps 1a and 2b: Map 1a depicts traditional reporting of mountain pine beetle (MPB)-caused damage areas across the Northern Region during peak year of recent outbreak in 2009 while Map 1b depicts the same damage by estimated impact severity within broad severity classes that provide for end-user information utility. Map 1b legend also has percent of total footprint area mapped occurrence within respective severity classes.

Table 2: Table depicting footprint area totals for pest activity by damage agent and severity classes mapped throughout the Northern Region with ADS in 2017.

Note: ***The importance of severity-weighted acres are described in Section 2 of this report.***

Damage Agent	Damage Footprint (acres) Total	Damage Severity (acres) Low	Moderate	High	Severity-Weighted Damage Area (acres)
Balsam Woolly Adelgid	9,148	4,156	3,929	1,063	2,592
Douglas-fir Beetle	37,678	30,808	4,987	1,884	5,788
Drought	535	535			41
Fir Engraver	61,047	56,068	4,844	135	5,938
Flooding-High Water	28	26	2		3
Larch Needle Cast	63,225	23,931	24,705	14,589	24,031
Larch Sawfly	1,693	1,454		240	530
Mountain Pine Beetle	36,128	26,941	7,645	1,542	5,967
Pine Engraver	2,244	1,456	604	184	482
Root Disease and Beetle Complex	9,162	8,004	1,052	105	1,045
Snow-Ice	6			6	6
Spruce Beetle	9,830	2,729	2,297	4,804	5,720
Unknown	1,092	8	81	1,003	1,029
Western Pine Beetle	2,801	2,259	520	23	356
Western Spruce Budworm	383,434	184,824		198,610	235,575
White Pine Blister Rust	4,680	4,383	212	86	488
Wind-Tornado/Hurricane	432			432	432
Total	**623,562**	**347,716**	**51,016**	**224,830**	**290,201**

Section 2: Issues with Footprint Area-Based Trend Assessment and a Severity-Weighted Area Solution

- Footprint area totals that aggregate spatial extent data do not consider that ADS data collection techniques allow for surveyor flexibility to map a given level of damage with widely divergent mapping extents. Thus, using footprint areas to depict pest activity or trends is suspect as ADS data are collected by means in which the severity and spatial extent information are confounded and linked.
- Determining valid pest trends with footprint area sums would require two conditions, neither of which are met with ADS data: 1) equal damage severities across comparison populations and 2) standardized data collected techniques where respective damage severities are estimated within consistent spatial bounds (e.g. points, small polygons, large polygons, etc.).
- Pest activity mapped with ADS incorporates damage and non-damaged areas within footprint areas and need to be scaled to a severity-weighted area statistic to exclude non-damage area for reasonable trend comparisons.
- Trend assessment should occur at subwatershed or greater spatial scales, only where flown coverage is sufficient, to reduce location attribution errors.

Traditional pest reporting has incorporated footprint area summations (i.e. total acres impacted) for broad-scale reporting of pest activity status and trend information for Forest, State, Regional,

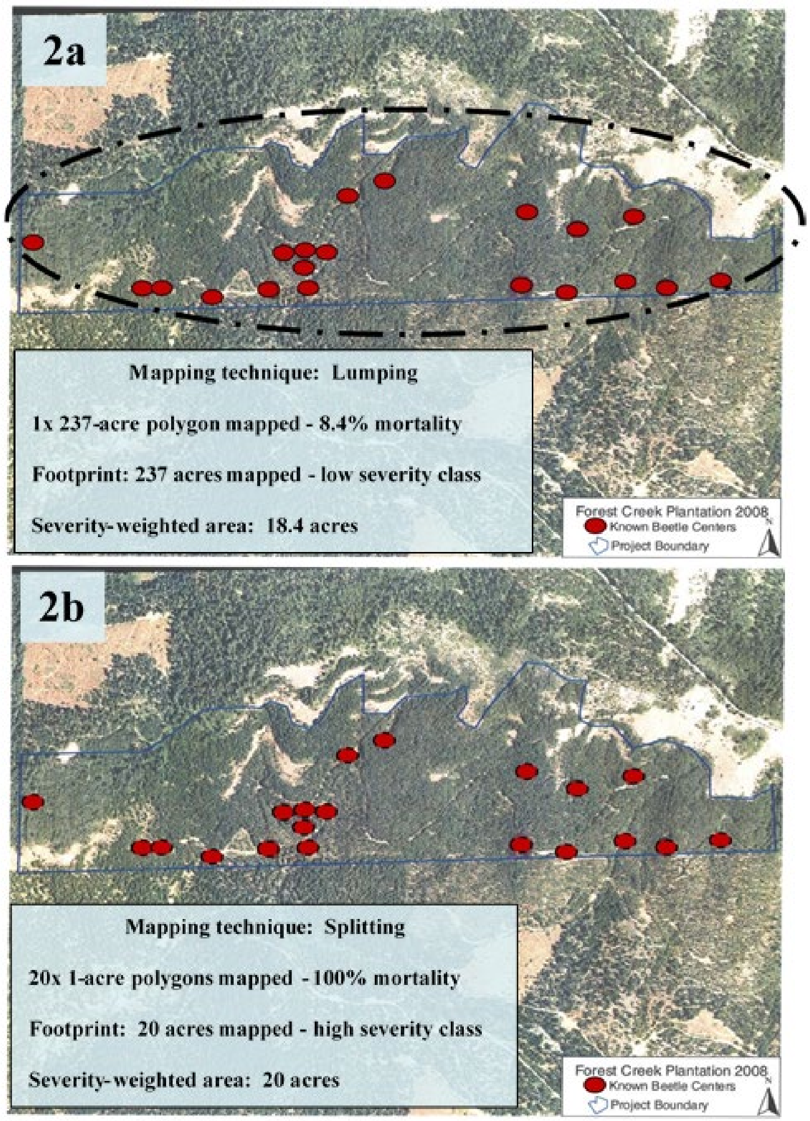


Figure 2a and 2b: Aerial photos detecting western pine beetle-caused mortality across the Forest Creek Plantations, Stanislaus National Forest showcasing how spatially flexible ADS mapping techniques can lead to widely divergent footprint area totals and invalid trend assessment even when mapping procedures are compliant with survey protocols.

and National conditions reports as well as State-level Forest Health Highlights (Map 1a; DNRC 2013; Hayes et al. 2016; Karel and Man 2017).

Trends aim to provide a general estimate of whether pest damage is increasing, decreasing, or occurring at similar levels relative to the prior year. Trend comparisons are one of the most useful products for end-users of ADS data; however, for footprint-acre comparisons to accurately depict increased or decreased pest activity two conditions must be met. First, severity of pest damage must be equivalent within mapped damage in each of the comparison populations. Second, ADS mapping techniques would need to record pest damages with a consistent mapping extent (e.g. point vs. localized polygon vs large polygon) to ensure footprint acres are equivalent for given levels of pest damage. When damage severities differ, or are the same but attributed with different mapping extents during ADS, trend comparisons using unadjusted footprint acres can be misleading or invalid.

Of the requirements listed above, the first is often discussed as a limitation of trend analysis with ADS. In this, footprint area summations do not reflect that one tree per acre mapped across ADS

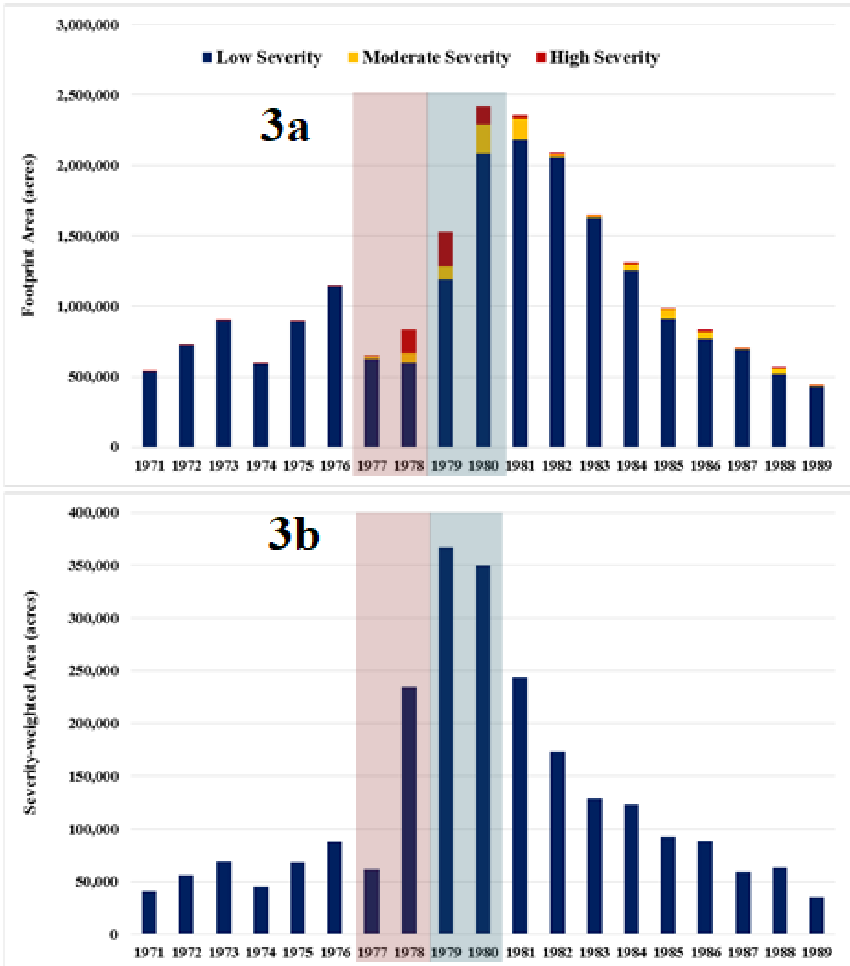


Figure 3a and 3b: Histogram with footprint area (3a) and severity-weighted area (3b) depictions of MPB-caused tree mortality mapped during the 1971-1989 outbreak period across the Northern Region. Pink highlighted years (3a vs 3b) shows minimal difference in MPB activity in 1977 vs 1978 (3a) that are captured with severity-weighted area calculations (3b). Blue highlighted area shows the wrong peak outbreak year was identified with a footprint area summation (3a) in 1980 when severity-weighted area (3b) shows activity peaked in 1979.

in 2009 across the Northern Region is substantially different than 200 trees per acre. Conversely, the second requirement is subtle and has not received rigorous discussion to-date. This point refers to the opposite condition where the same level of pest damage can be mapped with conservative or liberal (i.e. splitting vs lumping) footprint-area bounds. This occurs as ADS mapping protocols allow for surveyor flexibility to record pest damages in the most efficient manner possible for a given situation. In result, flexible survey protocols means that mapped damage extents are confounded with damage severity through an inverse relationship (e.g. as mapping extents increase footprint acres, damage severities decrease and visa-versa). Footprint area calculations do not reflect this reality.

The importance of this second requirement for valid trend assessment is depicted in Figures 2a and 2b. This example shows how lumping vs splitting techniques, each estimating damage correctly based on survey protocols, leads to an invalid footprint-area trend assessment. In this example, a footprint area comparison of the same damage mapped with divergent data collection techniques yields an 11.8-fold increase (237 vs 20 acres) in the lumping vs splitting data collected.

Taken further, annual footprint-area summations at a Regional-scale compound comparison issues as tens of thousands of damage areas are estimated with divergent degrees of lumping/splitting in mapping techniques.

This is shown in Table 3 for the 2009 MPB peak outbreak year data that was depicted in Section 1. This example shows footprint-area total across R1 in 2009 was heavily influenced by low

severity damages mapped with lumping techniques across large polygons > 250 acres. Overall, 87% of the footprint area summed from mapped points/polygons represents non-damaged areas and depicts the substantial inflation of total area that occurs when majority of damage is mapped at low severity.

Table 3: Table depicting contribution of splitting and lumping ADS mapping techniques on total footprint area for MPB damage recorded with ADS in 2009 across the Northern Region.

Point or Polygon Mapping Extent Category	Mapping Technique	Point or Polygon Damages Mapped (*n*)	Percent of Damages Mapped at Low Severity (< 10% mortality)	Footprint Area Contribution (acres)	Severity-Weighted Area (acres)	Percent of Total Footprint Area Representing Non-Damage
< 5 acres	Splitting	14,588	93%	31,095	3,115	90%
5-49.9 acres	Splitting	4,207	99%	84,301	6,886	92%
50-249.9 acres	Borderline	3,809	92%	501,523	48,872	90%
250-999.9 acres	Lumping	3,173	87%	1,527,325	171,206	89%
≥ 1000 acres	Lumping	903	72%	2,108,045	340,089	84%
Total		26,680		4,252,290	570,167	87%

Regional-level comparability issues with footprint-area totals are further illustrated with ADS data from the peak of the 1971-1989 MPB outbreak in the Northern Region. Trend comparison with footprint-area summations across years where different damage severities were mapped led to the wrong peak outbreak year to be identified and an incorrect annual trend assessment.

Specifically, footprint area totals in Figure 3a indicate similar footprint areas mapped with MPB-caused mortality in 1977 and 1978; however, severity distributions were substantially different as 4% of the 1977 footprint-area mapped had moderate or high-severity mortality levels vs. 29% in 1978. After considering severity information provided in Figure 3b, a substantial 4-fold increase in MPB pest activity occurred in 1978 relative to 1977. Similarly, footprint area mapped indicated the peak of the 1980s MPB outbreak was in 1980 (Figure 3a); however, further scrutiny of the severity information (Figure 3b) indicates the peak activity actually occurred the year prior, in 1979.

To promote valid trend comparisons, a severity-weighted statistic adjusts for different damage severity and spatial extent attributes collected during surveys. This statistic is calculated from the midpoint values of mortality ranges that define the qualitative classes, as described in Section 1, and scales all damages into a high-severity class baseline. In effect, area values for low and moderate classes are weighted to represent how much high-severity damage they incorporate based on relative midpoint differences (Figure 4). Classes are adjusted simply by multiplying areas of damage mapped by respective scaling factors provided in Figure 4.

The high-severity class is an ideal baseline for severity class-scaling for multiple reasons. First, there is greater confidence in the precision of observational ADS estimates that map high-severity damages relative to lower severity levels. Second, high-severity pest damage is what resource managers are most interested in monitoring. Third, using high severity class as a baseline provides a tangible statistic for reporting that indicates the total high-severity impact footprint that would occur from spatially aggregating all damage classes together.

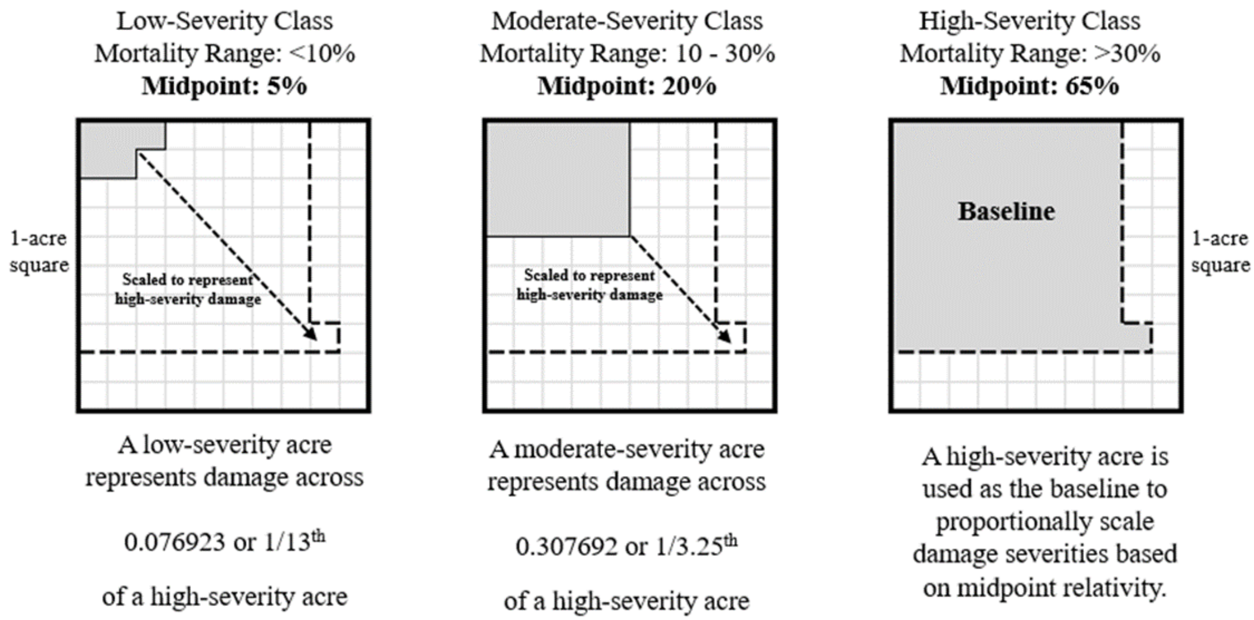


Figure 4: Conceptual figure showcasing the proportional relationship between severity class midpoints used to scale damage to a single statistic that incorporates area and severity information and can facilitate broad-scale comparisons.

After adjusting damage mapped by calculating severity-weighted acres, this statistic can be summed for reasonable trend estimation over space and/or time. To reduce spatial attribution errors, we recommend only estimating trends using broad spatial scales at the subwatershed or greater extents (i.e. County, Region, or National-levels). Further, trend comparison should only occur across populations where flown area coverage was similar.

This severity-weighted area statistic is beneficial for Regional-level reporting as is shown for pest damages mapped with ADS across the Northern Region in 2017 (Table 1). Comparisons of the severity-weighted area statistic estimates that Douglas-fir beetles caused 2-fold greater amount of damage relative to balsam woolly adelgids across the Region in 2017. Similar comparisons with 2016 data can provide end-users with reasonable trend assessment of individual pest damages as long as ADS coverage was similar enough to promote comparisons.

The preceding example represents a top-down reporting approach for coarse-level pest activity comparisons that are useful for Regional and National reporting. Similar comparisons with bottom-up reporting techniques and localized trend comparisons are also beneficial to meet local resource manager needs. A bottom-up reporting strategy can ensure flown area coverages overlap sufficiently for reasonable trend comparisons and is beneficial to show locations where localized pest trends differ from the overall Regional trend.

The minimum spatial scale recommended to summarize and compare pest activity trends from a bottom-up approach is a 6th level or Huc-12 subwatershed (Seaber et al. 1987). Subwatershed boundaries are based on fine-scale topographic features that can impact bark beetle population dispersal and disturbance levels (de la Giroday et al. 2012; Kaiser et al. 2012).

This unit is complementary to recent national-level assessments to provide guidance for restoration efforts (USDA FS 2011). Northern Region forested area subwatershed spatial extents are provided in Table 4.

Table 4: Area statistics for Northern Region Huc-12 Subwatersheds with a Forested Component.

Area Units	n	Mean Area	Median Area	Standard Deviation	Minimum Area	Maximum Area
Acres	~ 4,000	22,497	21,246	9,826	4,395	210,613
Square Miles	~ 4,000	35	33	15	7	329

Trend information categories are calculated within 'parent' subwatersheds and then are attributed to damage areas mapped (Maps 2a and 2b). Trend categories useful for end-users of forest health information are qualitatively and mathematically defined in Table 5.

Table 5: Qualitative and Mathematical Category Definitions for Subwatershed-level Trend Designation.

Trend Category	Qualitative Description (*Mathematical Definition*)
Decreased: Extinct Infestation	Damage decreased relative to prior year and is no longer active (*≥ 25% reduction from prior year & no current activity*)
Decreased: Active Infestation	Damage decreased relative to prior year and is still an active infestation (*≥ 25% reduction from prior year & current activity exists*)
Continued Infestation	Damage similar to estimates from the prior year (*± 25% of prior year's infestation*)
Increased from Active Infestation	Damage increased in areas with active infestation the prior year (*≥25% increase from prior year's infestation*)
Increased: New Infestation	Damage increased in a new area that was not active the prior year (*New locations with no prior year's infestation*)
Trend Not Comparable	Trend assessment not feasible with insufficient flown area coverage overlap (*± 75% flown area coverage relative to prior year*)

Bottom-up reporting can provide end-users information regarding localized trends, calculated at the subwatershed level, that are lost with a top-down reporting.

To illustrate local trend assessments, consider Map 2a which depicts MPB trend information in 2009 the peak year in which damage was mapped during recent MPB outbreak from 1999-2015 in the Northern Region. During this year, the trend calculated across the total Region indicated increased MPB activity (51% of the total 4.5 million acre footprint area mapped). However, bottom-up trend calculations can provide spatial locations for where activity continued at a similar rate (14%) or decreased (13%) in a manner useful for resource managers. This spatial information is especially valuable for years in which pest activity is increasing in some areas while decreasing in others (Maps 2a and 2b). This bottom-up reporting respects that not all areas are flown each year with ADS surveys by not calculating trends for those subwatersheds with insufficient multi-year coverage.

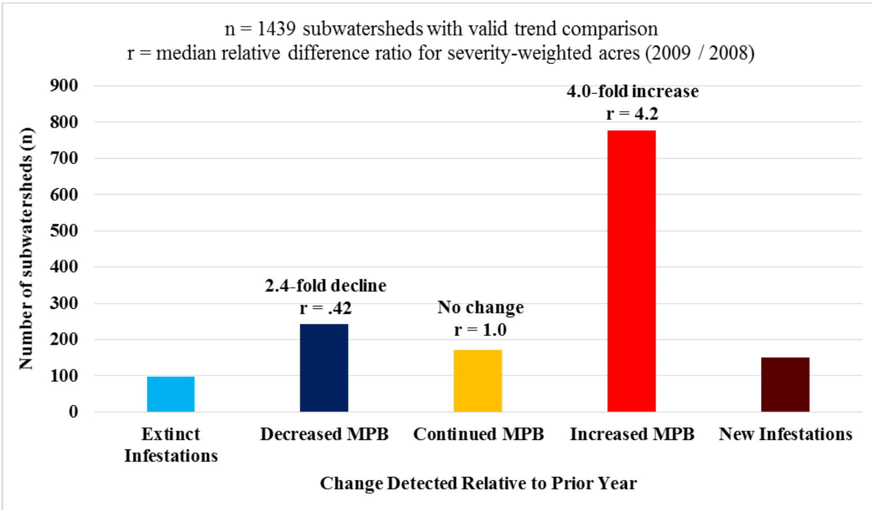


Figure 5: Subwatershed trend frequency by trend category and median magnitude of change in 2009 relative to 2008 across the Northern Region.

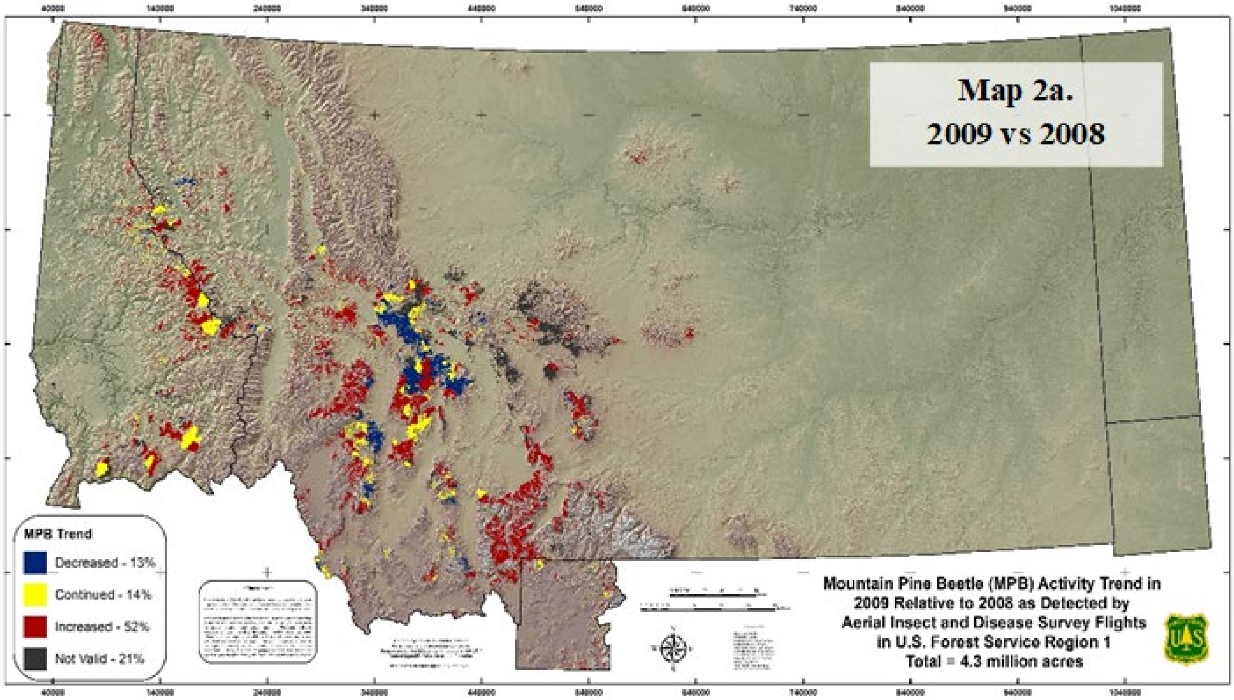
Statistics documenting the magnitude or strength of a given trend can also be calculated to support pest activity reporting. For example in 2009, subwatersheds with an increasing trend had a 4.2-fold median rate of expansion relative to the prior year and those with a declining trend decreased 2.4-fold (Figure 5).

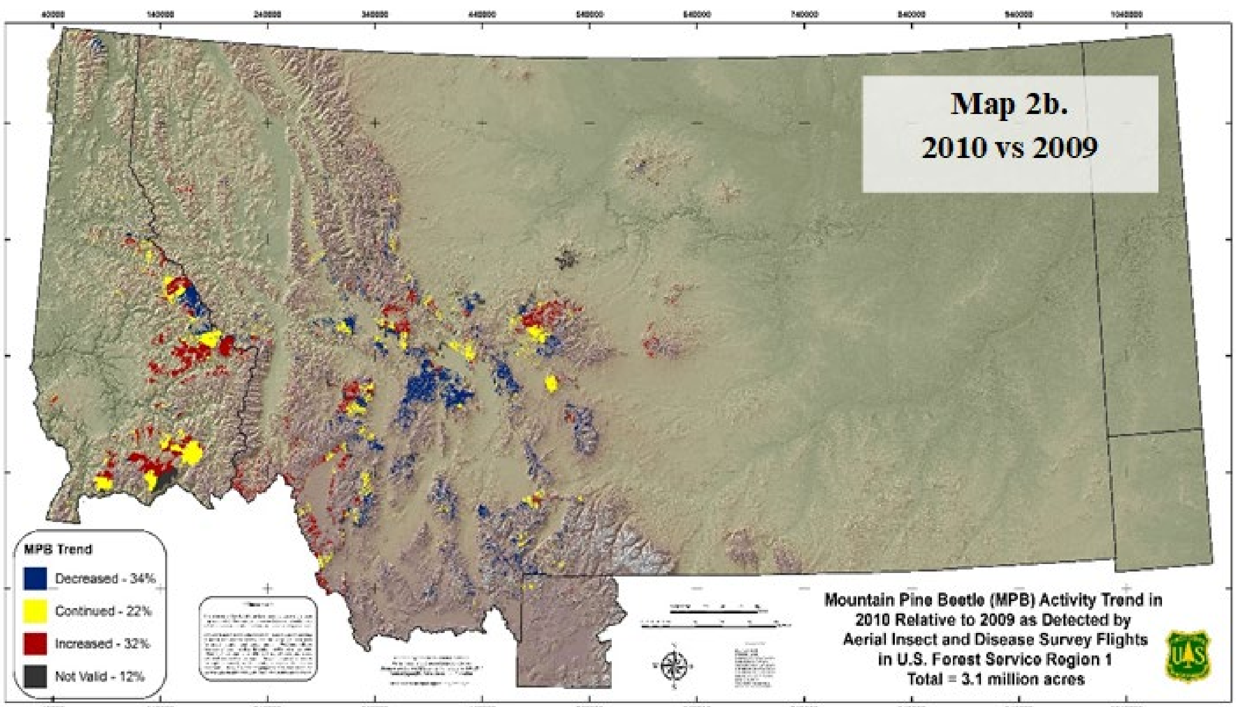
Section 3: Methods to Create Cumulative Pest Impact Assessment Products

- Forest Health Protection staff and end-users often create multi-year pest depictions that span the course of an outbreak.
- Cumulative outbreak products can be improved by aggregating severity classes over time to estimate multi-year pest impacts.
- Multi-year pest impact assessments are frequently requested to support Forest-level project prioritizations, Forest Plan revisions, landscape-scale project analyses, Farm Bill area-designations, Regional outbreak comparisons, and public outreach efforts.

Cumulative pest impact assessments are frequently created by end-users of forest health information. Examples of use range from Regional implementation of the National U.S. Forest Service Western Bark Beetle Strategy (USFS 2011) to incorporation into State-level Forest Health Highlight reports (DNRC 2013) and Forest-level project analysis areas (Egan and Lockman 2016). Two issues have repeatedly occurred regarding miss-use of ADS estimations within data processing steps. These include 1) aggregating yearly area sums without adjusting for spatial overlap and 2) not incorporating data from multiple damage agents columns in the ADS data collected with Digital Aerial Survey Mapper (DASM) procedures.

As such, FHP staff in multiple Regions have created Regional-level products to support end-user information requests, reduce miss-use of ADS data, and promote efficiency by reducing data processing workloads. These Regional-level products have included cumulative pest impact renditions and, in some cases, automated tools to process GIS algorithms that implement consistent methods across varied pest agents and/or time periods.





Map 2a and 2b: Mountain pine beetle damage mapped by Northern Region location in respective 2009 and 2010 years with trend calculated from prior-year's data.

Note: *Trends are calculated from ratio of severity-weighted acres mapped in a given year vs it's prior year within parent subwatersheds where sufficient overlap in flown area occurred.*

Cumulative product methods, similar to the Section 2 methods to facilitate comparisons, can be enhanced by utilizing a severity-weighted area statistic. Cumulative products that depict multi-year outbreaks further minimizes the importance of estimation and spatial attribution (location and extent) bias within ADS damage estimates as multiple years of overlapping damage mapped present converging lines of evidence to build multi-year outbreak damage estimates. These multi-year depictions from ADS could be augmented with other qualitative damage estimated from other sources, such as remotely sensed satellite imagery.

These cumulative products have utility for reporting objectives. As an example, consider impacts estimated from 1999-2015 during the most recent MPB outbreak period in the Northern Region (Map 3a-3d). This product provides information at a multi-year scale useful to resource managers.

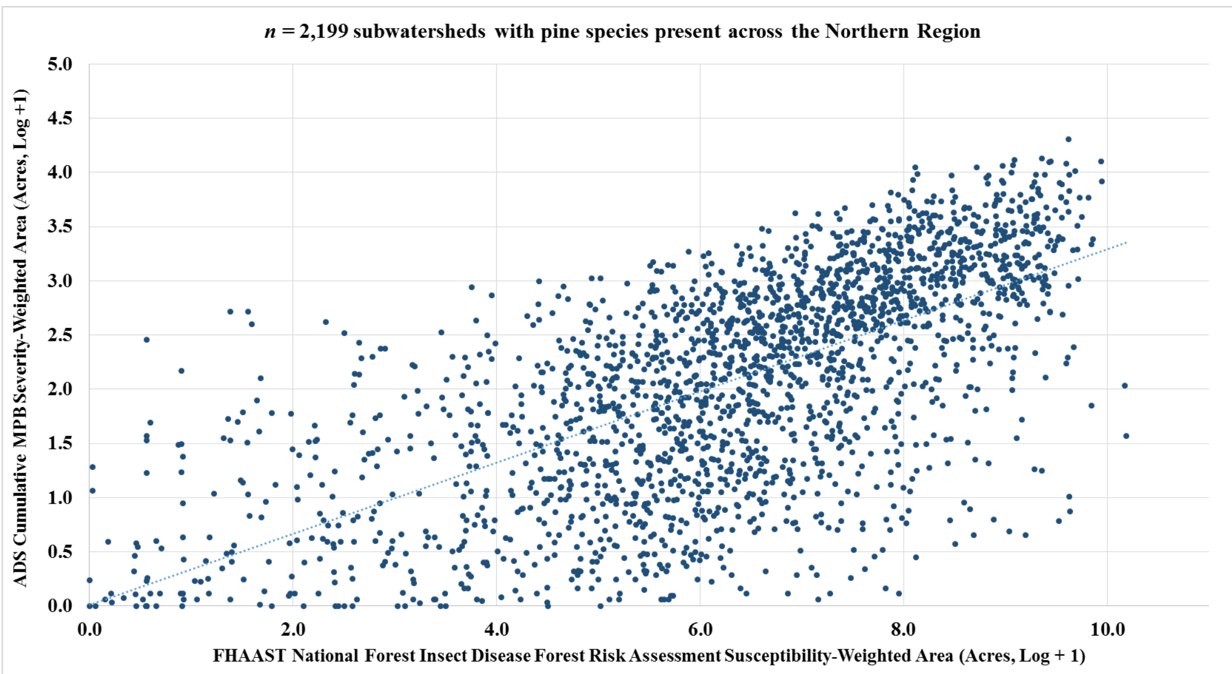
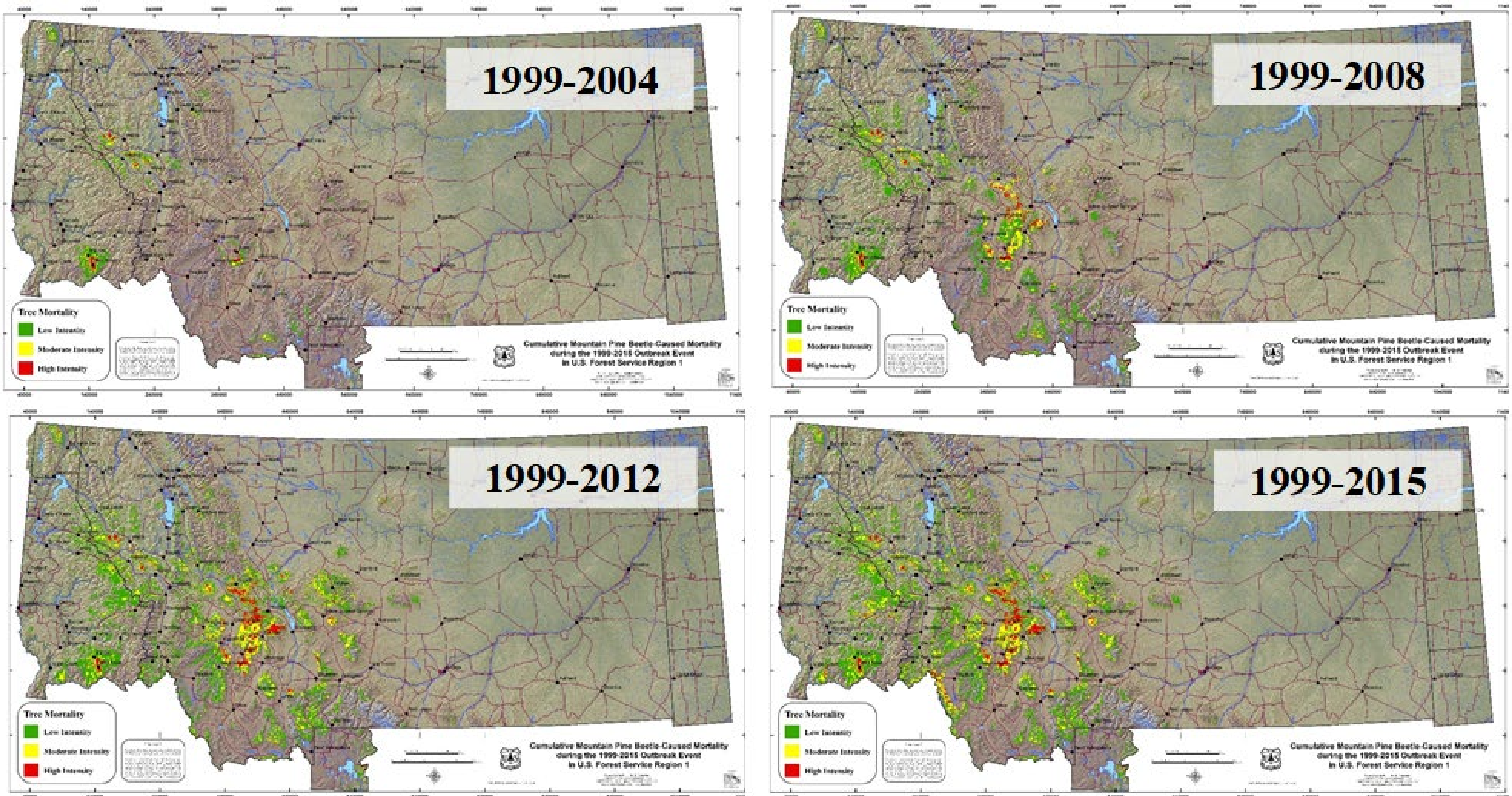


Figure 6: Scatter plot of statistically significant relationship between severity-weighted area summed across subwatersheds for MPB pest activity mapped with ADS from 1999-2015 in relation to 2002-vintage NIDFRA susceptibility data for MPB.

Taken further, summations of ADS severity-weighted acres from multiple years can be useful for statistical analysis. As an example, Egan et al. (manuscript in preparation) used this analysis strategy to validate 2002-vintage National Insect and Disease Forest Risk Assessment (NIDFRA, Krist et al. 2014) data for MPB across the Northern Region. Comparisons of these independent datasets at the subwatershed-level indicated strong positive relationship between 9.7 million acres of NIDFRA-estimated pine presence and degree of MPB susceptibility and the MPB outbreak occurrence and severity estimated by ADS from 1999-2015 (Figure 6). Geographically weighted regression modeling adjusted these data further for spatial autocorrelation to verify this relationship was significant across 89% of subwatersheds tested within the Northern Region.



Map 3a – 3d: Outbreak impact estimation depicting mortality progression at intervals from 1999-2015 caused by mountain pine beetles throughout the Northern Region.

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Appendix A. Steps to assign severity classes, calculate severity-weighted acres, and prepare fly/no fly layers from annual ADS geodatabase for assessment use
Methods to aggregate ADS data into severity classes for A1) historic data with trees per acre attributes and A2) newer data collection variables with percent mortality. A3) Methods to prepare fly/no fly layers (FNF).

Appendix A - Part A1. *For DASM damage assessment protocols (i.e. trees/acre variable to depict mortality and other damage intensity estimates).*

Example provided uses for mountain pine beetle for damage agent of interest.

1. **Ensure all damage data are aggregated in polygon-feature class format for analysis**:
   a. Data for analysis should include all mapped polygons and points buffered to set polygon extents. These steps should be completed in final Regional geodatabase of ADS damage.

2. **Select MPB data**: Complete for each yearly ADS geodatabase damage feature class; select by attributes where DCA1/2/3 indicates MPB damage agent
   a. Code: DCA1 = 11006 OR DCA2 = 11006 OR DCA3 = 11006

3. **Export feature class w/ only MPB data**: Export just the selection to new feature class (essentially, a state-of-the-art shapefile within a geodatabase) with the MPB_[Year] filename

4. **Attribute non-MPB data (from TPA1/2/3) to 0**: Select where DCA1 = 11006; then reverse selection to select all damage codes that aren't 11006. For this selection attribute the corresponding TPA1 values to 0.
   a. Select by attributes. Code: "DCA1" = 11006.
   b. Show only <u>selected</u> polygons
   c. Reverse selection which then would show all DCA1 codes that do not equal 11006.
   d. Use Field Calculator to set all TPA1 fields to '0' where DCA1 does not equal 11006.
   e. Do same for DCA2/TPA2 and DCA3/TPA3. Note if DCA3 does not come up w/ anything then need to set All TPA3 values to 0 w/ field calculator.

5. **Sum TPA1/2/3 to yield field w/ only MPB data**: Create a field (Double) called TPA_[year] and populate the field by summing the TPA1, TPA2, and TPA3 columns
   a. Clear any prior selections and show <u>all</u> records
   b. Use Field Calculator to Code: TPA1 + TPA2 + TPA3
   c. This will aggregate all the TPA values from any polygons that have different hosts for same damage agent into a single column for further assessment.

6. **Assign Severity classes**: Create a field (Integer field) MPB_Sev and populate the field with the categorical MPB severity codes (1 or 2 or 3)
   a. Use select by attributes then field calculator to fill field this newly created MPB_Sev field
   b. For each select by attributes make sure to Show only selected polygons before using field calculator
   c. Use select by attributes to select TPA_[year] <10 then populate corresponding fields w/ **1** value that signifies 'Low' damage severity class
   d. Use select by attributes to select TPA_[year] 10-30 then populate corresponding fields w/ **2** value that signifies 'Moderate' damage severity class

e. Use select by attributes to select TPA_[year] > 30 then populate corresponding fields w/ **3** value that signifies 'High' damage severity class

7. **Remove excess data fields**: Run the Delete fields tool and delete all fields except those listed.
   a. Fields to retain: TPA_[Year] ; MPB_Sev ; Host 1/2/3
   b. Create an Acres field (double) and use Calculate Geometry to populate acres

8. **Calculate the severity-weighted area**: multiply feature acres * severity-weighting scaling factor
   a. Create new field (double) called SevAc[year] - i.e. for 1999 would be SevAcre99
   b. Use select by attribute tool to select all MPB_Sev = 1 (Low) polygons
      i. Show only selected polygons
      ii. For only selected polygons, use Field Calculator to population SevAc[Year] field by multiplying Acres field by **.07692308**
      iii. Do same selection this time for MPB_Sev = 2 (Mod) polygons, then use Field Calculator to population SevAc[Year] field by multiplying Acres field by **.30769231**
      iv. Do same selection this time for MPB_Sev = 3 (High) polygons, then use Field Calculator to population SevAc[Year] field by multiplying Acres field by **1.0**

Appendix A - Part A2. *For data attributed with DMSM protocols (with percentage estimates for and other damage intensity estimates): Similar methods as for Part A1 except 1) DCA1/2/3 fields don't exist and there is only one damage agent per record and 2) percent mortality categories are used to attribute severity classes rather than trees/acre.*

1. **Ensure all damage data are aggregated in a feature class for analysis**:
   a. Data for analysis should include all mapped polygons and points buffered to set polygon extents. These steps should be completed in final Regional geodatabase of ADS damage. The USFS Northern Region Forest Health Protection (FHP) crew built a python toolbox for ArcGIS Desktop to run these processes (ADS_PestDamageEstimate.pyt/AppendixA). The raw ADS Damage dataset is the input for the tool.

2. **Add the necessary processing and output attribute fields:**
    a. ACRES_FINAL (Double)
    b. SeverityWeightedAcres (Double)
    c. Severity_Factor (Double)
    d. Severity_Classs (Text, length 15)
    e. Damage_Class (Text, length 15)
    f. SWA_Mortality (Double)
    g. SWA_NonMortality (Double)
    h. SWA_Defoliation (Double)
    i. MidPoint (Short)

3. **Consolidate two similar attribute fields into one:**
    a. Select all records where the HOST_GROUP_CODE > 0
        i. Employ the Field Calculator to copy Host Group (Codes) into Host (Codes)
            A. HOST_CODE = HOST_GROUP_CODE
            B. HOST = HOST_GROUP

4. **Assign Severity classes for polygons and points**: Employ the newly created Severity_Class (text) attribute field and Severity_Factor (Double) attribute field
    a. Assign the appropriate values to the Severity Class and Severity Factor attribute fields based on PERCENT_AFFECTED_CODE and NUMBER_OF_TREES_CODE attribute fields, using the Select by Attributes tool:
        i. PERCENT_AFFECTED_CODE = 1 OR PERCENT_AFFECTED_CODE = 2 OR NUMBER_OF_TREES_CODE = 1 OR NUMBER_OF_TREES_CODE = 2 OR NUMBER_OF_TREES_CODE = 3
            A. [Severity Class] = "LOW"
            B. [Severity_Factor] = 5/65
        ii. PERCENT_AFFECTED_CODE = 3 OR NUMBER_OF_TREES_CODE = 4
            A. [Severity_Class] = "MODERATE"
            B. [Severity_Factor] = 20/65
        iii. PERCENT_AFFECTED_CODE = 4 OR PERCENT_AFFECTED_CODE = 5 OR NUMBER_OF_TREES_CODE = 5
            A. [Severity_Class] = "HIGH"
            B. [Severity_Factor] = 1.0

5. **Assign a mid-point value by Percent Affected Class or Trees per Point Class**: Use the recently created MidPoint attribute field (Short) and populate the field with mid-point percent damage severity values for polygons and points. This step is needed to support cumulative damage renditions in further analyses.
    a. For each PERCENT_AFFECTED_CODE, Select by Attributes the classification code (1-5, respectively) and use Field Calculator to populate the MidPoint field with following midpoint percentages:
        i. Class 1 (Very Light 1-3%): **2**
        ii. Class 2 (Light 4-10%): **7**
        iii. Class 3 (Moderate 11-29%): **20**
        iv. Class 4 (Severe 30-50%): **40**

v. Class 5 (Very Severe 50-100%): **75**

b. For each NUMBER_OF_TREES_CODE Class, Select by Attributes the classification code (1-5, respectively) and use Field Calculator to populate the MidPoint field with following midpoint values:
   i. Class 1 (1 tree): **2**
   ii. Class 2 (2-5 trees): **2**
   iii. Class 3 (6-15 trees): **7**
   iv. Class 4 (16-30 trees):**20**
   v. Class 5 (>30 trees): **40**

6. **Attributing Defoliation:**
   a. Select by Attribute where [DAMAGE_TYPE_CODE] = 14, utilize the Field Calculator to:
      i. [Severity_Factor] = 1
      ii. [Severity_Class] = "HIGH"
      iii. [Damage_Class] = "Defoliation"
   b. Select by Attribute where [DAMAGE_TYPE_CODE] = 13 OR [DAMAGE_TYPE_CODE] = 12, utilize the Field Calculator to:
      i. [Severity_Factor] = 0.2
      ii. [Severity_Class] = " LOW"
      iii. [Damage_Class] = "Defoliation"
   c. These values were further adjusted for the intensity of the infestation:
      i. When [PERCENT_AFFECTGED_CODE] = 1 OR [PERCENT_AFFECTGED_CODE] = 2
         A. Values from steps 6a and 6b multiplied by 5/65 (~0.076923)
            1. 6a [Severity_Factor] = 5/65
            2. 6b [Severity_Factor] = 0.2*5/65
      ii. When [PERCENT_AFFECTGED_CODE] = 1 OR [PERCENT_AFFECTGED_CODE] = 3
         A. Values from steps 6a and 6b multiplied by 20/65 (~0.307692)
            1. 6a [Severity_Factor] = 20/65
            2. 6b [Severity_Factor] = 0.2*20/65
      iii. When [PERCENT_AFFECTGED_CODE] = 4 OR [PERCENT_AFFECTGED_CODE] = 5
         A. Values from steps 6a and 6b multiplied by 65/65 (1)
            1. 6a [Severity_Factor] = 1
            2. 6b [Severity_Factor] = 0.2

7. **Calculate raw Acreage and the Severity-Weighted Acres**:
   a. Using the Field Calculator with the newly created ACRES_FINAL (Double) attribute field
      i. [ACRES_FINAL] = !shape.area@acres!
         A. OR right-click on the ACRES_FINAL attribute field and select Calculate Geometry (ensure no records are selected)
            1. Property: Area

2. Units: Acres US [ac]

b. Using the Field Calculator with the newly created SeverityWeightedAcres (Double) attribute field

i. [SeverityWeightedAcres] = [ACRES_FINAL] * [Severity_Factor]

8. **Attributing Mortality and Non-Mortality and all three SWA_(Damage type) attribute fields:**

a. Select by Attribute where [DAMAGE_TYPE_CODE] = 2 OR [DAMAGHE_TYPE_CODE] = 11

i. [SWA_Mortality] = [SeverityWeightedAcres]

ii. [Damage_Class] = "Mortality"

b. Select by Attribute where [DAMAGE_TYPE_CODE] = 3 OR [DAMAGE_TYPE_CODE] = 4 OR [DAMAGE_TYPE_CODE] = 5 OR [DAMAGE_TYPE_CODE] = 6 OR [DAMAGE_TYPE_CODE] = 7 OR [DAMAGE_TYPE_CODE] = 8 OR [DAMAGE_TYPE_CODE] = 9 OR [DAMGE_TYPE_CODE] = 18

i. [SWA_NonMortality] = [SeverityWeightedAcres]

ii. [Damage_Class] = "Non-Mortality"

c. Select by Attribute where [Damage_Class] = 'Defoliation'

i. [SWA_Defoliation] = [SeverityWeightedAcres]

9. **Remove excess data fields**: Run the Delete Fields tool and delete all fields except those listed.

a. Fields to **RETAIN**:

i. CREATED_DATE

ii. REGION_ID

iii. LABEL

iv. HOST_CODE

v. HOST

vi. DCA_CODE

vii. DCA

viii. DAMAGE_TYPE_CODE

ix. DAMAGE_TYPE

x. NUMBER_OF_TREES_CODE

xi. NUMBER_OF_TREES_DESC

xii. TREE_COUNT

xiii. COLLECTION_MODE

xiv. PERCENT_AFFECTED_CODE

xv. PCT_AFFECTED

xvi. ACRES_FINAL

xvii. SeverityWeightedAcres

xviii. Severity_Factor

xix. Severity_Class

xx. Damage_Class

xxi. SWA_Mortality

xxii. SWA_NonMortality

xxiii. SWA_Defoliation
xxiv. MidPoint

Appendix A - Part A3. ***Steps to prepare Fly no Fly layers for use in further analysis steps***

1. For the Fly/No Fly dataset - the critical attribute field is the FLOWN field. This should be coded 1 for areas flown and 0 for areas not flown.
   a. Select by Attributes where [FLOWN] = 1 and export the selection to a new feature class in the same geodatabase where the ADS Damage dataset is located; naming it R1R4_FLOWN_year
   b. Use Delete field tool to delete all unnecessary fields retaining:
      i. START_DATE
      ii. END_DATE
      iii. REGION_ID
      iv. FLOWN
   c. Create a new attribute field named, acres (Double), and use the Calculate Geometry to populate acres.
   d. Use Dissolve tool to get rid of overlapping flown area polygons ensuring that no area is calculated for acreage multiple times.

2. Finally, add the R1R4_FLOWN_year and the R1R4_ADS_Damage_year datasets into one geodatabase for further analysis
   a. The geodatabase should be named: R1R4_ADS_year_Final

Do same for all years would like to calculate trends or all year's during outbreak period for cumulative impact estimations.

Appendix B. Analysis to crosswalk trees/acre mortality data into percent-based severity classes

Purpose: Statistical analysis took place to determine the best breakpoints with trees/acre (TPA) response that were associated with 10% and 30% mortality thresholds that are class breakpoints. Findings present a crosswalk to stratify continuous TPA ADS data into percent-based low, moderate, and high severity classes depicted in Table 1, Section 1 of this report.

Data Utilized: Field-collected plot data was used to assess relationship between percent vs trees/acre mortality rates. Plots (*n*=329 plots, 0.1 to 2-acres in size, surveying 30,386 individual trees) were obtained from across the western U.S. as part of a longitudinal analysis assessing *Dendroctonus* spp.-caused mortality across yellow pine-dominated forest types (Egan et al. 2020, in preparation; Table B1). Plots represented ADS data well as they had variable spatial extents, mortality levels, and forest densities.

Variability Analysis: First, a descriptive assessment of variability within TPA, as a function of percent mortality, occurred across all data points and at 10% and 30% mortality points of interest. Variability in TPA response was limited from 0-19% mortality rates then progressively increased in data points $\geq$ 20%. Range of TPA mortality associated with 10% mortality rates was 5-25 TPA and for 30% was 7-125 TPA. At very high percent mortality rates this range was even higher. As example, at 75% mortality the TPA mortality ranged from 43 to 264 TPA. This supports having the highest severity class at no greater than 30% to facilitate a crosswalk with TPA data. Even with variation observed, a positive, linear association occurred between these variable supported further modeling.

Statistical Analysis: Regression models were used to determine ideal TPA thresholds for low, moderate, and high percent-based severity classes (Table 1). Three simple regressions modeled relationship between TPA response and percent mortality predictor across 1) the entire dataset (natural log transformed response and predictor; see Figure 1); 2) at a localized data window near 10%; and 3) at a localized data window near 30%. Then, lower 95th% confidence interval was calculated for percent mortality data points of interest (x=10% and x=30%) and averaged from each of the three models and rounded to nearest base-10 (Table B2). These averaged TPA numbers represent best-available TPA crosswalk thresholds corresponding with 10% and 30% percent-based severity class thresholds.

Validation: A confusion matrix calculated accuracy of categorically assigning TPA values, based on crosswalk thresholds calculated with above statistical analysis, into percent-based severity classes (Table B3). Overall, findings indicate high level of overall accuracy with 84% of all plots were assigned into the correct percent-based severity classes based on TPA mortality values.

Conclusion: Converting trees per acre data into qualitative, percent-based impact classes described in Section 1 is reasonable based on this crosswalk process. A high degree of validated accuracy was found with measured ground data. Based on the variation assessment, it is not advised to use trees per acre data to estimate severity classes without collapsing those classes into broad categories (such as <10%, 10-30%, and >30% or broader).

Table B1: Summary of studies compiled for meta-analysis of *Dendroctonus* spp.-attacked plots across western U.S.

Citation	Location	Survey Period Range	Beetle Pressure	Total # Plots (n)	Pines Sampled	Median Plot Size (ac)	Bark Beetle Spp.	Avg. Mortality (%)	Max % Mortality
Graham et al. 2016	Black Hills, SD & WY	1994-2010	High	84	15,394	1.2	MPB	15%	96%
Egan et al. 2010	Warner Mtns, CA	2001-2007	High	36	1,264	0.3	MPB, WPB	5%	49%
Hood et al. 2016	Northern Rocky Mtns, MT	2005-2012	High	42	794	0.2	MPB	23%	93%
Egan et al. 2011	Central Sierra Nevada, CA	1991-1996	High	72	10,436	1.0	JPB	36%	91%
Fettig et al. 2018 Unpub	Southern Sierra Nevada, CA	2013-2016	High	66	822	0.1	WPB	64%	100%
Briggs Unpub	Front Range, CO	2008-2011	High	17	656	0.3	MPB	7%	50%
Hall & Davies 1968	Warner Mtns, CA	1961-1965	High	4	1,404	1.0	MPB	28%	90%
Egan & Lockman 2018	Bitterroot Mtns, MT	2012-2015	High	24	1,094	0.2	MPB	7%	67%
	Total Values			345	31,864				

Table B2: Table of linear regression modeled trees per acre (TPA) mortality at respective 10% and 30% predictor data points from studies compiled for meta-analysis of *Dendroctonus* spp.-attacked plots across western U.S.

Model Type	Mortality Predictor	Intercept	Parameter estimate	Parameter Std. Error	Estimated TPA	Lower 95% CI
Untransformed data 5-15% window	10%	7.529	59.222	38.811	13.5	9.6
Nat. log response & predictor - all data	10%	4.867	0.984	0.019	12.9	12.9
Mean					**13.2**	**11.2**
Untransformed data 20-40% window	30%	1.083	176.296	103.845	54.0	22.8
Nat. log response & predictor - all data	30%	4.867	0.984	0.019	37.3	38.0
Mean					**45.6**	**30.4**

Table B3: Confusion matrix depicting frequency of correctly assigning trees per acre data into percent mortality-based severity classes using TPA crosswalk thresholds with research plots that surveyed *Dendroctonus* spp.-attack across the western U.S.

		Percent-based Severity Classes Predicted by TPA Values			
	Severity Class	**TPA estimated low-severity class (< 10% mortality)**	**TPA estimated moderate-severity class (10-30% mortality)**	**TPA estimated high-severity class (> 30% mortality)**	**Recall (%)**
	< 10%	**123**	21	1	85%
Actual	**10-30%**	4	**32**	17	60%
	> 30%	0	9	**122**	93%
	Precision (%)	97%	52%	87%	**84%**

Citations for data used in trees/acre to percent mortality crosswalk analysis

Egan, J.M., Jacobi, W.R., Negron, J.F., Smith, S.L., Cluck, D.R., 2010. Forest thinning and subsequent bark beetle-caused mortality in northeastern California. For. Ecol. and Mgmt. 260, 1832-1842.

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Egan, J., Lockman, B. 2018. Stand conditions associated with mountain pine beetle-attack in long-term forest health plots near Lake Como, Bitterroot National Forest. FHP report in progress as of 5/1/18.

Egan, J., Coleman, T., Fettig, C., Graham, J., Patterson, D., Jenne, J. et al. 2018. Meta-analysis of structural-based resistance to Dendroctonus spp.-attack in yellow pine forests across the western U.S. Data analysis complete and manuscript in preparation as of 5/1/18.

Graham, R.T., Asherin, L.A., Battaglia, M.A, Jain, T.B., Mata, S.A. 2016. Mountain pine beetles: A century of knowledge, control attempts, and impacts central to the Black Hills. General Technical Report RMRS-GTR-353. U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station. 206 p.

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**** Fettig et al. and Briggs et al. publications were being drafted when this report was written and should be considered available but unpublished data.**

Appendix C. Geospatial processing steps to use severity-weighted acres for trend analysis
Trends are calculated within a given year relative to the year prior, within parent subwatersheds in which damages were mapped to promote bottom-up reporting.

Part A. Create the Union of Required Datasets

1. Complete steps in Appendix A (calculates severity-weighted acres, classifies the damage types, and reduces extra data columns in attribute table) for each year in which trends will be calculated. To calculate this year, one will need to run this year's and last year's data through these processes delineated in Appendix A; for there must be a comparison to establish a trend.

2. The USFS Northern Region Forest Health Protection (FHP) crew built a python toolbox tool for ArcGIS Desktop to run these processes (ADS_PestDamageEstimate.pyt/AppendixC).
    a. Data inputs are:
        i. HUC12 subwatersheds dataset delineating watershed boundaries
        ii. PADUS dataset that includes all jurisdictional boundaries desired
        iii. USFS Regional Boundary dataset
        iv. ADS Damage dataset for this year (after processing through App. A)
        v. ADS Damage dataset from last year (after processing through App. A)
        vi. ADS Flown dataset for this year (after processing through App. A)
        vii. ADS Flown dataset from last year (after processing through App. A)
    b. Output:
        i. Navigate and/or create the output/working geodatabase where all intermediate and final datasets will be located, naming it: R1R4_ADS_year_TrendsAnalysis

3. The tool will combine the five datasets: HUC12, PADUS, USFS Regional Boundary, ADS Damage for given year, and ADS Flown for given year for both years creating two datasets.

Part B. Update Acreage Values – both raw and Severity-Weighted Acres (SWA) while populating the Damage Class SWA fields.

1. The tool recalculates the raw acreage
    a. [ACRES_FINAL] = !shape.area@acres!
        i. This calculates acreage in the same manner as would utilizing the Calculate Geometry tool on the attribute table in ArcGIS Desktop.
    b. [SeverityWeightedAcres] = [ACRES_FINAL] * [Severity_Factor]

2. Select by attribute where [Damage_Class] = 'Defoliation'
    a. [SWA_Defoliation] = [SeverityWeightedAcres]

3. Select by attribute where [Damage_Class] = 'Mortality'
    a. [SWA_Mortality] = [SeverityWeightedAcres]

4. Select by attribute where [Damage_Class] = 'Non-Mortality'
    a. [SWA_NonMortality] = [SeverityWeightedAcres]

5. The tool now deletes unnecessary fields created by the union of five datasets.

Part C. Creating Summary Statistics Tables for each damage agent and type.

1. The tool creates a list of all the unique damage agents, both by pest (i.e. Douglas-Fir Beetle) and damage class (Defoliation) by searching the [DCA_CODE] and [Damage_Class] attribute fields.

2. The tool then selects all records that satisfy each unique damage agent record and where the attribute field [FLOWN] = 1, creating over 40 summary statistics tables that include the subwatershed identification code, subwatershed name, total acreage of the subwatershed, sum of raw acres by agent by subwatershed, and the sum of the SWA by agent by subwatershed. It also extracts the Fly/No-Fly acreage values by subwatershed.

Part D. Calculate the FNF difference validation ratio

1. The tool creates two new attribute fields in the HUC12 subwatershed dataset named [FlyNoFly_year] for both this year and last year.

2. The tool then populates the new attribute fields from the appropriate Summary Statistics tables [SUM_ACRES_FINAL] attribute created in Part C.
   a. All records retaining a NULL value after importing values from the summary statistics tables are converted to zero.

3. The tool now creates a new attribute field named: [FlyNoFly_(this_year)v(last_year)]
   a. The ratio is created by dividing this year's coverage acres by last year's coverage acres where last year's coverage acres > 0.
      i. All records retaining a NULL value after calculating the FNF difference ratio are converted to zero.

4. Another new attribute field is created to analyze whether the ratio reveals a value indicating that sufficient aerial detection survey overlap occurred between the years in question to provide a valid trend: [FlyNoFly_OK]
   a. If [FlyNoFly_(this_year)v(last_year)] ≥ 0.75 AND [FlyNoFly_(this_year)v(last_year)] ≤ (1/0.75) then [FlyNoFly] =1; otherwise, [FlyNoFly] = 0

Part E. Extract damage agent summary statistics table data to the HUC12 subwatershed dataset and calculate the agent trends values.

1. For each agent found within the unique damage agents list created in Part C, four new attribute fields will be created:
   a. [(Agent)_(Agent code)_(last year)]; i.e. Avalanche_50015_2017
   b. [(Agent)_(Agent code)_(this year)]; i.e. Avalanche_50015_2018
   c. [(Agent)_(Agent code)_SWA_(this year)v(last year)]; i.e. Avalanche_50015_SWA_2018v2017
   d. [(Agent)_(Agent code)_Trend_(this year)v(last year); i.e. Avalanche_50015_Trend_2018v2017

2. The first two fields listed above will be populated with the [SUM_SeverityWeightedAcres] attribute field from the appropriate summary statistics table created in Part C.
   a. All records retaining a NULL value after importing values from the summary statistics tables are converted to zero.

3. The third field (SWA) is calculated by dividing this year's SWA value by last year's SWA value where last year's value > 0.
   a. All records retaining a NULL value after the calculation are converted to zero.

4. The fourth field (Trend) is a classification following these thresholds:
   a. Valid Trend, No Damage: The area had sufficient flown area coverage between the years in question to establish a damage trend, just no damage was detected in those areas.
      i. Select by Attribute, Create new Selection: [(Agent)_(Agent code)_(last year)] = 0 AND [(Agent)_(Agent code)_(this year)] = 0 AND [FlyNoFly_OK] = 1
      ii. Attribute/Category code to populate Trend field with: **-1**

   b. Trend Not Valid: there is not sufficient flown area coverage to determine trend
      i. Select by Attributes, Create new Selection: [FlyNoFly_OK] = 0
      ii. Attribute/Category code to populate Trend field with: **0**

   b. Increased Infestation: MPB activity was greater than 25% of severity-weighted acres detected in prior year
      i. Select by Attributes, Create new Selection: [FlyNoFly_OK] = 1 AND [(Agent)_(Agent code)_SWA_(this year)v(last year)] > (1/0.75)
      ii. Attribute/Category code to populate Trend field with: **1**

   c. Increased and New Infestations:
      i. Select by Attributes, Create new Selection: [FlyNoFly_OK] = 1 AND [(Agent)_(Agent code)_(last year)] = 0 AND [(Agent)_(Agent code)_(this year)] > 0
      ii. Attribute/Category code to populate Trend field with: **2**

   d. Continued Infestation: Year of interest severity-weighted acres are within 25% of prior year
      i. Select by Attributes, Create new Selection: [FlyNoFly_OK] = 1 AND [(Agent)_(Agent code)_SWA_(this year)v(last year)] ≥ 0.75 AND [(Agent)_(Agent code)_SWA_(this year)v(last year)] ≤ (1/0.75)
      ii. Attribute/Category code to populate Trend field with: **3**

   e. Decreased Infestations: MPB activity was reduced more than 25% of severity-weighted acres detected the prior year
      i. Select by Attributes, Create new Selection: [FlyNoFly_OK] = 1 AND [(Agent)_(Agent code)_SWA_(this year)v(last year)] < 0.75 AND [(Agent)_(Agent code)_(last year)] > 0 AND [(Agent)_(Agent code)_(this year)] > 0

ii. Attribute/Category code to populate Trend field with: **4**

f. Decreased & Extinct Infestations: MPB activity occurred the prior year with none detected within the year of interest
   i. Select by Attributes, Create new Selection: [FlyNoFly_OK] = 1 AND [(Agent)_(Agent code)_(last year)] > 0 AND [(Agent)_(Agent code)_(this year)] = 0
   ii. Attribute/Category code to populate Trend field with: **5**

5. This categorization scheme allows for two display schemes at subwatershed level:
   a. Simple display:
      i. No Trend valid (0 code), Increasing (1&2), Continued (3), Decreasing (4&5)
   b. Complex display:
      i. No Trend valid (0 code), New infestations (2), Increased infestations - not new (1), Continued (3), Decreasing - not extinct (4), and Extinct (5)

Part F. Join the multi-year SWA and Trend data back to the ADS Damage year of interest dataset

1. The appended HUC12 subwatershed dataset from Part E will be joined by attribute field back into the ADS Damage polygons dataset
   a. The join is performed using the [HUC12] attribute field which is the HUC12 identification code
   b. Only records where [FLOWN] =1 are exported from the ADS Damage polygons dataset with the join creating a final output of "R1R4_ADS_(year)_TrendAnalysis" dataset.
   c. Finally, the tool deletes unnecessary fields.

Part G. Calculation of median trends across spatial extent chosen

1. Python 2.7 (the version used to write the code for ArcGIS Desktop) also does not have a median function, so the USFS Northern Region Forest Health Protection (FHP) crew built a python toolbox tool for ArcGIS Desktop including a median function (ADS_PestDamageEstimate.pyt/Calculate_Median).
   a. Navigate to the dataset from which the Medians are to be calculated
      i. The tool was specifically built for the R1R4_ADS_(year)_TrendAnalysis dataset
   b. Choose which administrative area attribute field to summarize by
      i. Damage_Class
      ii. FORESTNAME (most researchers want this one)
      iii. DISTRICTNAME
      iv. STATE
      v. COUNTY
      vi. DNRC_Zone (for state of Montana)
      vii. USFS Region
   c. Indicate the output table folder name and table name; click ok to run

d. The output is a csv table that calculates the median value for each damage agent by each boundary indicated in the administrative area selection for both the increasing (Trend = 1) and decreasing (Trend = 4) infestations.